Drivers of Global Carbon Dioxide Emissions: International Evidence

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2015

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NB:This is the accepted version. The pusblished version is available via Inderscience Publishers.

http://www.inderscienceonline.com/doi/abs/10.1504/IJGE.2015.075145

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Abstract

Studies pertaining to the effects of economic growth on the environment generally focused on diverse relationships between carbon dioxide, economic growth and energy consumption. This paper contributes to the literature by determining the effects of the US and China's emissions on several economies carbon dioxide discharges from 1960 to 2010. The analysis uses a cointegration procedure proposed by Saikkonen and Lütkepohl. The study further applies the Granger causality test to test for causal links. The results of the study demonstrate that the US Granger causes emissions of ten economies under investigation. Additionally, China Granger causes fourteen economies carbon dioxide discharges. In essence, the US and China are tasked with the duty of accelerating programmes attempting to reduce global carbon dioxide emissions due to their influential standpoint.

JEL: Q50

Keywords: carbon dioxide emissions; economic growth; Granger causality; green taxation.

1 Introduction

Economic growth is a major goal for many economies. Developing economies attempt to leave no stone left unturned in their attempts to industrialize and transform into economic giants. Despite the fact that economic growth is desirable, environmental impacts have been detrimental. Many economies today are faced with problems such as land degradation by the mining sector; pollution of water sources; disruption of aquatic life and more importantly intense carbon dioxide emissions. According to Xu & Lin (2015) between 1980 and 2012, carbon dioxide emissions in China's transport sector increased by approximately 9.7 times with an average annual growth rate of 7.4%. This raises concern for the Chinese government because it means the country is the largest emitter of carbon dioxide and also an enormous contributor to the greenhouse effect. Recently, China postulated a target of 40-45% reduction in carbon dioxide emissions by the year 2025. China is now under pressure to find effective methods that can turn this endeavour into reality. It is important to highlight that the methods postulated by China lately have been termed to be ineffective in the long run especially the emissions–trading system.

Previous studies focused intently on verifying affiliations between economic growth and carbon dioxide emissions. This paper deviates from this perspective by attempting to determine the effect of the US and China's emissions on other economies discharges. The literature generally focused on emissions each country produces but fails to address the effects of developed economies emissions on other countries' carbon dioxide discharges. This study therefore contributes to the literature by examining carbon dioxide emissions of fifty economies from 1960 to 2010 and relates their discharges with the world's top economies (China and the US). The Granger causality test is used to determine the direction of causation between two emissions series. In this manner, the study reveals whether the US or China drive the world's carbon dioxide emissions. The investigation further uses the Saikkonen and Lütkepohl cointegration test to determine long term series affiliations. The results of this study show that the US Granger causes ten economies emissions series. China drives fourteen economies emissions as from 1960 to 2010. The rest of this paper is structured as follows. Next is the literature review. This will be followed by methodology and time series evidence. Finally a conclusion of the study follows with conclusion and implications.

2 Literature Review

Researchers have been interested in the dynamic relationships between economic growth, energy consumption and carbon dioxide emissions. Alshehry & Belloumi (2015) aimed to examine the dynamic causal relationships between energy consumption, prices and economic growth in Saudi Arabia based on a demand side approach. The study also applied the Johansen multivariate cointegration approach. Accordingly, the results proved that there exist long run relationships between energy consumption, energy prices, carbon dioxide emissions and economic growth. Causality results proved causation from energy consumption to economic growth and carbon dioxide emissions. There was also evidence of bidirectional causality between carbon dioxide emissions and economic growth. However, in the short run there was causation from carbon dioxide emissions to energy consumption and economic growth. In conclusion, the authors supported the energy-led growth hypothesis in Saudi Arabia. The results implied that regulations aimed at reducing energy consumption and minimizing carbon dioxide emissions may not adversely affect economic growth. In this era were countries are under pressure to limit carbon dioxide emissions, the fear of affecting economic growth adversely always arises. Even though on paper the effects of minimizing carbon discharges may not be severe on economic growth, other macroeconomic variables such as employment levels are in jeopardy. Economies need to address this issue before enforcing carbon dioxide emissions thoroughly. In contribution, to the literature Lee & Brahmasrene (2013) examined the influence of tourism on economic growth and carbon dioxide emissions using unit root tests and cointegration models. The study examined a panel of European Union countries from 1988 to 2009. The results of the study demonstrated that economic growth has significant effects on carbon dioxide emissions. The results are plausible because as an economy expands, energy consumption should result in high carbon dioxide emissions. Logically, this should lead to a positive long run relationship between the variables.

In contribution, Wang (2013a) examined the importance of differential output growth from the combustion of fossil fuels. The study surveyed Chinese and US carbon dioxide emissions over the period 1990 to 2009. The results of the investigation proved that output growth raises carbon dioxide discharges. Contributively, Omri (2013) examined the nexus between carbon dioxide emissions, energy consumption and economic growth using simultaneous equations models for fourteen MENA countries over the period 1990 to 2011. The results showed that there exist causal relationships between energy consumption and economic growth. The study supported the occurrence of causality from energy consumption to carbon dioxide emissions without feedback. Therefore, the research postulates that energy consumption drives carbon dioxide emissions. If there was feedback relationship between the variables, it would be difficult for policy makers to make decisions because the results will imply that carbon dioxide emissions drive energy consumption. In theoretical and practical terms, to reduce carbon discharges the obvious direction is to minimize consumption of fossil fuels especially coal.

Zhang & Cheng (2009) investigated the existence and direction of causality between economic growth, energy consumption and carbon dioxide emissions in China using a multivariate model. The results postulated causality from energy consumption to carbon dioxide emissions over the period 1960 to 2007. The authors suggested that regulations on carbon dioxide emissions can be enforced without necessarily hindering economic growth. The results are good news for China because the country wants to progress economically and also reduce emissions by 40-45% in 2025. The concern is, theoretically the impact of policy implications on economic growth may not be significant, but in practical terms when factors such as reduction in energy usage and green taxes are enforced strongly, the outcomes may deviate from theoretical calculations. Nonetheless, China should continuously monitor carbon emissions as she is the world's largest emitter of carbon dioxide.

In Turkey, Soytas & Sari (2009) found out that carbon dioxide emissions seem to Granger cause energy consumption but the reverse causality was nullified. The annulled causal relationship between income and carbon emissions may postulate that to reduce emissions, the Turkish economy is not obliged to sacrifice economic growth following Soytas & Sari (2009). In extension to the literature, Wang (2012b) examined the relationship between carbon dioxide emissions from oil and GDP using panel data from 1971 to 2007. The study reported that in low economic growth regimes, economic growth adversely affected carbon emissions from oil. However, in medium economic growth regimes, economic growth was found to impact positively on carbon dioxide emissions growth.

The concern for most economies is reducing carbon dioxide emissions especially huge emitters such as China and India. Most economies prefer using green taxation to minimize carbon dioxide emissions. Loganathan et al. (2014) contributed to the literature by examining the effects of carbon taxation over the period 1974 to 2010 in Malaysia. The study applied cointegration and causality approaches to determine the long term relations between the variables. Causality analysis proved that there were causal interactions between carbon taxation and carbon dioxide emissions. The results of this study are similar to those of Zhixin & Ya (2011). The authors noted that carbon tax had the potential to stimulate economic growth for most eastern Chinese provinces as from 1999 to 2008.

An overview of the reviewed literature specifies that much attention has been channelled to the dynamic relationships between carbon dioxide emissions, economic growth and energy consumption. Most studies generally applied cointegration and causality tests to validate the Environmental Kuznets Curve (Alshehry & Belloumi, 2015; Lee & Brahmasrene, 2013; Wang, 2013a; Zhang & Cheng, 2009; Soytas & Sari 2009; Wang, 2012b). Green taxation has proved to be sustainable as it has the capacity to stimulate economic growth in Eastern Chinese provinces. The literature fails to address the relationship between carbon dioxide emissions among economies. This study fills the gap by examining carbon emissions for the US and China from 1960 and 2010. It is noted well that the US and China are the largest economies in the world and their emissions may have potential effects on other countries carbon emission. The expectation is that if any of the two economies continuously produces exports, carbon dioxide emissions will rise. In consequence, the country procuring the machinery and expertise will develop industrially and this will result in more emissions. This study uses the Augmented Dickey Fuller test, Saikkonen and Lütkepohl cointegration approach and the Granger causality test to validate these relations. The results proved that all countries trend positively with both the US and China's emissions. However, the long run causal results demonstrate that China's emissions Granger cause fourteen economies discharges. The reverse causality nonetheless shows that China's emissions are led by six economies' carbon emissions. Similarly, the US emissions led ten economies emissions and the reverse causality demonstrated that only Mexico and Nicaragua drive US emissions.

3 Materials and Methods

This study examines data for fifty countries from 1960 to 2010. The focus of this investigation is to determine emissions relationship between such economies and carbon dioxide discharges produced by the US and China. The data was obtained from Global Economy (http://www.theglobaleconomy.com/) which is a website dedicated to monitoring and disseminating macroeconomic data to researchers. Carbon dioxide emissions were quantified in tonnes (t). Before proceeding with the empirical analysis, this study commences by examining the data for unit roots. Even though there are several techniques for testing for non-stationarity such as the KPSS test and the Phillips & Perron test, the Augmented Dickey Fuller test (ADF) (see Dickey & Fuller, 1979) is selected since it has higher statistical power and is the most applied statistical test for determining the order of integration following Asemota and Bala (2011). Eviews 7 was used to test for stationarity. The results of the stationarity test are presented by Table 1 and 2.

Table 1: Carbon Dioxide Emissions Stationarity- Augmented Dickey Fuller Test Results

Country	ADF Test Statistics		
Argentina	$-2.698808_{-[4.152511]}$	$-2.698808_{-[3.502373]}$	$-2.698808_{-[3.180699]}$
Bahamas	$-2.154741_{-[4.152511]}$	$-2.154741_{-[3.502373]}$	$-2.154741_{-[3.180699]}$
Barbados	$-3.468529_{-[4.152511]}$	$-3.468529_{-[3.502373]}$	$-3.468529_{-[3.180699]}$
Belize	$-3.145638_{-[4.152511]}$	$-3.145638_{-[3.502373]}$	$-3.145638_{-[3.180699]}$
Bermuda	$-2.627085_{-[4.152511]}$	$-2.627085_{-[3.502373]}$	$-2.627085_{-[3.180699]}$
Bolivia	$-2.161230_{-[4.152511]}$	$-2.161230_{-[3.502373]}$	$-2.161230_{-[3.180699]}$
Brazil	$-1.784733_{-[4.152511]}$	$-1.784733_{-[3.502373]}$	$-1.784733_{-[3.180699]}$
Canada	$-1.032705_{-[4.152511]}$	$-1.032705_{-[3.502373]}$	$-1.032705_{-[3.180699]}$
Chile	$-0.983834_{-[4.152511]}$	$-0.983834_{-[3.502373]}$	$-0.983834_{-[3.180699]}$
Colombia	$-2.033297_{-[4.152511]}$	$-2.033297_{-[3.502373]}$	$-2.033297_{-[3.180699]}$
Costa Rica	$-1.773968_{-[4.152511]}$	$-1.773968_{-[3.502373]}$	$-1.773968_{-[3.180699]}$
Cuba	$-1.615093_{-[4.152511]}$	$-1.615093_{-[3.502373]}$	$-1.615093_{-[3.180699]}$
Dominica	$^{**}4.429357_{-[3.584743]}$	$^{**}4.429357_{-[2.928142]}$	$^{**}4.429357_{-[2.602225]}$
Ecuador	$^{**}0.019085_{-[3.584743]}$	$^{**}0.019085_{-[2.928142]}$	$^{**}0.019085_{-[2.602225]}$
El Salvador	$1.505174_{-[4.152511]}$	$1.505174_{-[3.502373]}$	$1.505174_{-[3.180699]}$
Grenada	$-1.427037_{-[4.152511]}$	$-1.427037_{-[3.502373]}$	$-1.427037_{-[3.180699]}$
Guatemala	$-1.653552_{-[4.152511]}$	$-1.653552_{-[3.502373]}$	$-1.653552_{-[3.180699]}$
Guyana	$^{**}-2.585905_{-[3.584743]}$	$^{**}-2.585905_{-[2.928142]}$	$^{**}-2.585905_{-[2.602225]}$
Haiti	$-2.162003_{-[4.152511]}$	$-2.162003_{-[3.502373]}$	$-2.162003_{-[3.180699]}$
Honduras	$-0.310856_{-[4.152511]}$	$-0.310856_{-[3.502373]}$	$-0.310856_{-[3.180699]}$
Jamaica	$-2.035391_{-[4.152511]}$	$-2.035391_{-[3.502373]}$	$-2.035391_{-[3.180699]}$
Mexico	$-2.115752_{-[4.152511]}$	$-2.115752_{-[3.502373]}$	$-2.115752_{-[3.180699]}$
Nicaragua	$-2.596140_{-[4.152511]}$	$-2.596140_{-[3.502373]}$	$-2.596140_{-[3.180699]}$
Panama	$-1.192520_{-[4.152511]}$	$-1.192520_{-[3.502373]}$	$-1.192520_{-[3.180699]}$
Paraguay	$-2.058368_{-[4.152511]}$	$-2.058368_{-[3.502373]}$	$-2.058368_{-[3.180699]}$
Peru	$0.938881_{-[4.152511]}$	$0.938881_{-[3.502373]}$	$0.938881_{-[3.180699]}$
Saint Lucia	$0.297122_{-[4.152511]}$	$0.297122_{-[3.502373]}$	$0.297122_{-[3.180699]}$
Suriname	$-2.348721_{-[4.152511]}$	$-2.348721_{-[3.502373]}$	$-2.348721_{-[3.180699]}$
Trinidad & Tobago	$1.701194_{-[4.152511]}$	$1.701194_{-[3.502373]}$	$1.701194_{-[3.180699]}$

Uruguay	-2.344373-[4.152511]	-2.344373-[3.502373]	-2.344373-[3.180699]
Venezuela	-3.026477-[4.152511]	-3.026477-[3.502373]	-3.026477-[3.180699]
Algeria	**-0.292398-[3.584743]	**-0.292398-[2.928142]	**-0.292398-[2.602225]
Angola	0.930283-[4.152511]	0.930283-[3.502373]	0.930283-[3.180699]
Benin	1.112110-[4.152511]	1.112110-[3.502373]	1.112110-[3.180699]
Japan	-1.2926803-[4.152511]	-1.2926803-[3.502373]	-1.2926803-[3.180699]
Cameroon	-3.636495-[4.152511]	-3.636495-[3.502373]	-3.636495-[3.180699]
Chad	-1.216344-[4.152511]	-1.216344-[3.502373]	-1.216344-[3.180699]
Ivory Coast	2.480051-[4.152511]	2.480051-[3.502373]	2.480051-[3.180699]
Kenya	0.045192-[4.152511]	0.045192-[3.502373]	0.045192-[3.180699]
Liberia	-2.164546-[4.152511]	-2.164546-[3.502373]	-2.164546-[3.180699]
Madagascar	-3.825266-[4.152511]	-3.825266-[3.502373]	-3.825266-[3.180699]
Mauritania	-1.787607-[4.152511]	-1.787607-[3.502373]	-1.787607-[3.180699]

Table 1 (continued)

Country	ADF Test Statistics		
Morocco	1.726850-[4.152511]	1.726850-[3.502373]	1.726850-[3.180699]
Niger	-2.083071-[4.152511]	-2.083071-[3.502373]	-2.083071-[3.180699]
Rep. Congo	-3.467718-[4.152511]	-3.467718-[3.502373]	-3.467718-[3.180699]
Senegal	2.800756-[4.152511]	2.800756-[3.502373]	2.800756-[3.180699]
South Africa	-2.478771-[4.152511]	-2.478771-[3.502373]	-2.478771-[3.180699]
Hong Kong	-1.084960-[4.152511]	-1.084960-[3.502373]	-1.084960-[3.180699]
India	1.139594-[4.152511]	1.139594-[3.502373]	1.139594-[3.180699]
Israel	-1.649141-[4.152511]	-1.649141-[3.502373]	-1.649141-[3.180699]
US	-2.488882-[4.152511]	-2.488882-[3.502373]	-2.488882-[3.180699]
China	2.038258-[4.152511]	2.038258-[3.502373]	2.038258-[3.180699]

The figure outside the brackets is the ADF statistic.
The results are based on the model $\Delta y_t = \alpha + \beta_t + \gamma y_{t-1} + \sum_{i=1}^{k} \delta_i \Delta y_{t-1} + \varepsilon_t$.
-[4.152511] is the critical value at 1% level
-[3.502373] is the critical value at 5% level
-[3.180699] is the critical value at 10% level
(**) Due to data properties, the unit root test for these countries was carried out at unit root level and the test equation excluded the intercept in this case. Hence critical values are as follows: -[3.584743] critical value at 1% level; -[2.928142] critical value at 5% level and -[2.602225] critical value at 10% level.

The results of the above ADF unit root test demonstrate that the series is suitable for further empirical analysis. This is proved by test statistics which are greater than the critical values at different critical levels (that is, 1%, 5% and 10% level). In this study, cointegration and causality methods will be applied. This study commences with the cointegration test because the assumption is that Granger causality will surface if the observations are cointegrated.

3.1 Testing Long Run Relationships Between Emissions Series

Previous studies focused intently on using the Johansen cointegration test as a technique for testing long run affiliations. This paper deviates from this perspective by applying the recent cointegration method proposed by Saikkonen & Lütkepohl (2000). Cointegrated variables will be attracted to each other therefore resulting in long run affiliations. Even though the Johansen cointegration test and the Saikkonen & Lütkepohl test are almost similar, there are technical differences. Firstly, the Saikkonen and Lütkepohl test is different technically because it estimates the deterministic term first and then subtracts it from the time series observations unlike the Johansen method. Saikkonen & Lütkepohl (2000) commenced their model by considering a $VAR\ (p)$ process of the form:

$$y_t = v + A_1 y_{t-1} + \cdots + A_p y_{t-p} + \varepsilon_t \qquad t = p+1, p+2, \ldots,$$

Following Saikkonen & Lütkepohl (2000) allow A_J to be $n \times n$ coefficient matrices while ε_t is an $n \times 1$ is a stochastic error term assumed to be a martingale difference sequence with $E(\varepsilon_t | \varepsilon_{s,} s < t) = 0$. The non-stochastic positive definite conditional covariance matrix was defined as $E(\varepsilon_t \grave{\varepsilon}_t | \varepsilon_{s,} s < t) = \Omega$. Consequently, the final error correction model formed by subtracting y_{t-1} on both sides of the $VAR\ (p)$ above is

$$\Delta\tilde{y}_t = v + \Pi\tilde{y}_{t-1} + \sum_{j=1}^{p-1} \Gamma_j \Delta\tilde{y}_{t-j} + \varepsilon_t \qquad t = p+1, p+2, \ldots,$$

The definition of terms is $\Pi = -(I_n - A_1 - \cdots - A_p)$ while $\Gamma_j = -(A_{j+1} + \cdots + A_p)$ $(j = 1, \ldots, p-1)$. The test validates if $H(r_0): rk(\Pi) = r_0$.

3.2 Testing for Granger Causality

Multiple studies have applied the Granger causality to validate causal links between the variables. The Granger causality is applied in this paper to test for causation between two emissions series. The reason for selection is that the Granger causality test is more reliable when examining data with a wide span (in this case, 50). Granger (1969) assumed that when testing for causality the future cannot impinge on the past. Therefore Granger (1969) relied on past and present data to make predictions on a future variable. The postulation by Granger (1969) is that if A_t is stationary stochastic process, then $\bar{A}_t$ will then represent the set of past values while $\bar{\bar{A}}_t$ will be the set of past and present values. By implication, allow e_1 to represent Chinese or US emissions at time t. Therefore e_2 will portray any of the country's emissions at time t. The resulting error correction models following Granger et al. (2000) will then be:

$$\Delta e_{1t} = \alpha_0 + \delta_1(e_{1t-1} - \gamma e_{2t-1}) + \sum_{i=1}^{k} \alpha_{1t}\Delta e_{1t-i} + \sum_{i=1}^{k} \alpha_{2i}\Delta e_{2t-i} + \varepsilon_{1t}$$

$$\Delta e_{2t} = \beta_0 + \delta_2(e_{1t-1} - \gamma e_{2t-1}) + \sum_{i=1}^{k} \beta_{1t}\Delta e_{1t-i} + \sum_{i=1}^{k} \beta_{2i}\Delta e_{2t-i} + \varepsilon_{2t}$$

4 Empirical Results

The Saikkonen and Lütkepohl test was carried out at 90%, 95% and 99% critical levels using JMulti (4) statistical package. The results show that there is a long run relationship between all the countries' carbon emissions and the two countries carbon discharges (the US and China). Tables 2 and 3 represent the results of the cointegration test. Note that ρ-values less than the critical levels of 90%, 95% and 99% represent cointegration.

Table 2: Results of the Saikkonen and Lütkepohl Cointegration Test (US)

Country	r_0	LR	90%	95%	99%	ρ-value	r_0	LR	90%	95%	99%	ρ-value
Argentina	0	7.8600	13.880	15.760	19.710	0.56360[1,2,3]	1	0.6900	5.470	6.790	9.730	0.87310[1,2,3]
Bahamas	0	3.4500	13.880	15.760	19.710	0.96620[3]	1	1.6500	5.470	6.790	9.730	0.62110[1,2,3]
Barbados	0	9.3800	13.880	15.760	19.710	0.39810[1,2,3]	1	1.8000	5.470	6.790	9.730	0.58510[1,2,3]
Belize	0	11.8200	13.880	15.760	19.710	0.19910[1,2,3]	1	1.5700	5.470	6.790	9.730	0.64150[1,2,3]
Bermuda	0	7.2700	13.880	15.760	19.710	0.63120[1,2,3]	1	2.5500	5.470	6.790	9.730	0.42250[1,2,3]
Bolivia	0	4.8800	13.880	15.760	19.710	0.88020[1,2,3]	1	0.5900	5.470	6.790	9.730	0.90020[2,3]
Brazil	0	5.0200	13.880	15.760	19.710	0.86880[1,2,3]	1	0.1700	5.470	6.790	9.730	0.98470[3]
Canada	0	17.8400	13.880	15.760	19.710	0.02190[1,2,3]	1	1.1200	5.470	6.790	9.730	0.76140[1,2,3]
Chile	0	5.5900	13.880	15.760	19.710	0.81620[1,2,3]	1	0.8700	5.470	6.790	9.730	0.82630[1,2,3]
Colombia	0	5.0800	13.880	15.760	19.710	0.86360[1,2,3]	1	1.2000	5.470	6.790	9.730	0.73930[1,2,3]
Costa Rica	0	6.5100	13.880	15.760	19.710	0.71930[1,2,3]	1	0.0060	5.470	6.790	9.730	0.99750
Cuba	0	2.3200	13.880	15.760	19.710	0.99380	1	0.8500	5.470	6.790	9.730	0.83130[1,2,3]
Dominica	0	6.7900	13.880	15.760	19.710	0.68740[1,2,3]	1	0.4000	5.470	6.790	9.730	0.94230[2,3]
Ecuador	0	19.2400	13.880	15.760	19.710	0.01220[1,2,3]	1	1.6600	5.470	6.790	9.730	0.61910[1,2,3]
El Salvador	0	3.0800	13.880	15.760	19.710	0.97890[3]	1	0.3200	5.470	6.790	9.730	0.95930[3]
Grenada	0	4.5400	13.880	15.760	19.710	0.90630[2,3]	1	1.1700	5.470	6.790	9.730	0.74690[1,2,3]
Guatemala	0	5.0200	13.880	15.760	19.710	0.86880[1,2,3]	1	0.0200	5.470	6.790	9.730	0.99950
Guyana	0	4.7100	13.880	15.760	19.710	0.89350[1,2,3]	1	1.2900	5.470	6.790	9.730	0.71350[1,2,3]
Haiti	0	8.9300	13.880	15.760	19.710	0.44380[1,2,3]	1	0.8700	5.470	6.790	9.730	0.82740[1,2,3]
Honduras	0	4.6400	13.880	15.760	19.710	0.89870[1,2,3]	1	0.0300	5.470	6.790	9.730	0.99900
Jamaica	0	11.5200	13.880	15.760	19.710	0.21830[1,2,3]	1	1.2900	5.470	6.790	9.730	0.71360[1,2,3]
Mexico	0	8.4600	13.880	15.760	19.710	0.49520[1,2,3]	1	1.0000	5.470	6.790	9.730	0.79160[1,2,3]
Nicaragua	0	5.1700	13.880	15.760	19.710	0.85540[1,2,3]	1	2.9500	5.470	6.790	9.730	0.35170[1,2,3]
Panama	0	3.4300	13.880	15.760	19.710	0.96730[3]	1	1.5800	5.470	6.790	9.730	0.64020[1,2,3]
Paraguay	0	8.7500	13.880	15.760	19.710	0.46350[1,2,3]	1	0.1500	5.470	6.790	9.730	0.98750[3]
Peru	0	2.9500	13.880	15.760	19.710	0.98240[3]	1	1.6700	5.470	6.790	9.730	0.61600[1,2,3]
Saint Lucia	0	6.1900	13.880	15.760	19.710	0.75440[1,2,3]	1	0.3100	5.470	6.790	9.730	0.96060[3]
Suriname	0	5.0200	13.880	15.760	19.710	0.86860[1,2,3]	1	1.7300	5.470	6.790	9.730	0.60120[1,2,3]
Tri. & Tob.	0	4.1900	13.880	15.760	19.710	0.92930[2,3]	1	0.2400	5.470	6.790	9.730	0.97360[3]
Uruguay	0	5.9800	13.880	15.760	19.710	0.77630[1,2,3]	1	1.4700	5.470	6.790	9.730	0.66620[1,2,3]
Venezuela	0	9.2700	13.880	15.760	19.710	0.40850[1,2,3]	1	1.7800	5.470	6.790	9.730	0.59070[1,2,3]
Algeria	0	9.4700	13.880	15.760	19.710	0.38820[1,2,3]	1	1.3000	5.470	6.790	9.730	0.71160[1,2,3]
Angola	0	3.6800	13.880	15.760	19.710	0.95660[3]	1	3.0300	5.470	6.790	9.730	0.33860[1,2,3]
Benin	0	4.3100	13.880	15.760	19.710	0.92180[2,3]	1	3.1500	5.470	6.790	9.730	0.32060[1,2,3]
Japan	0	8.1800	13.880	15.760	19.710	0.52700[1,2,3]	1	0.6000	5.470	6.790	9.730	0.89570[1,2,3]
Cameroon	0	9.9800	13.880	15.760	19.710	0.34040[1,2,3]	1	1.7200	5.470	6.790	9.730	0.60480[1,2,3]
Chad	0	2.9600	13.880	15.760	19.710	0.98210[3]	1	1.0000	5.470	6.790	9.730	0.79310[1,2,3]
Ivory Coast	0	5.6800	13.880	15.760	19.710	0.80710[1,2,3]	1	2.4100	5.470	6.790	9.730	0.44980[1,2,3]
Kenya	0	6.2500	13.880	15.760	19.710	0.74820[1,2,3]	1	2.1800	5.470	6.790	9.730	0.49780[1,2,3]
Liberia	0	3.3300	13.880	15.760	19.710	0.97080[3]	1	0.6200	5.470	6.790	9.730	0.89130[1,2,3]
Madagascar	0	10.9500	13.880	15.760	19.710	0.25910[1,2,3]	1	1.4100	5.470	6.790	9.730	0.68350[1,2,3]
Mauritania	0	6.0700	13.880	15.760	19.710	0.76680[1,2,3]	1	2.3200	5.470	6.790	9.730	0.46770[1,2,3]

Morocco	0	7.3200	13.880	15.760	19.710	0.62560^{1,2,3}	1	0.0300	5.470	6.790	9.730	0.99920
Niger	0	5.0800	13.880	15.760	19.710	0.86360^{1,2,3}	1	2.6600	5.470	6.790	9.730	0.40150^{1,2,3}
Rep. Congo	0	10.0000	13.880	15.760	19.710	0.33790^{1,2,3}	1	2.0300	5.470	6.790	9.730	0.53220^{1,2,3}
Senegal	0	7.8200	13.880	15.760	19.710	0.56820^{1,2,3}	1	1.0500	5.470	6.790	9.730	0.77780^{1,2,3}
South Afr.	0	5.9800	13.880	15.760	19.710	0.77680^{1,2,3}	1	2.5300	5.470	6.790	9.730	0.42720^{1,2,3}
Hong Kong	0	4.6600	13.880	15.760	19.710	0.89770^{1,2,3}	1	2.3100	5.470	6.790	9.730	0.47100^{1,2,3}
India	0	5.9600	13.880	15.760	19.710	0.77820^{1,2,3}	1	0.7300	5.470	6.790	9.730	0.86300^{1,2,3}
Israel	0	4.1500	13.880	15.760	19.710	0.93210^{2,3}	1	1.6200	5.470	6.790	9.730	0.62990^{1,2,3}

Superscripts 1, 2, 3 show statistical significance at 90%, 95%, and 99% critical levels. LR = Likelihood Ratio

Table 3: Results of the Saikkonen and Lütkepohl Cointegration Test (China)

Country	r_0	**LR**	**90%**	**95%**	**99%**	**ρ-value**	r_0	**LR**	**90%**	**95%**	**99%**	**ρ-value**
Argentina	0	6.3900	13.880	15.760	19.710	0.73220^{1,2,3}	1	4.5600	5.470	6.790	9.730	0.16030^{1,2,3}
Bahamas	0	3.5200	13.880	15.760	19.710	0.96360^{2,3}	1	0.2600	5.470	6.790	9.730	0.97090^{3}
Barbados	0	12.2900	13.880	15.760	19.710	0.17130^{1,2,3}	1	0.7700	5.470	6.790	9.730	0.85320^{1,2,3}
Belize	0	13.5700	13.880	15.760	19.710	0.11120^{1,2,3}	1	0.4800	5.470	6.790	9.730	0.92420^{2,3}
Bermuda	0	9.5500	13.880	15.760	19.710	0.38060^{1,2,3}	1	0.4700	5.470	6.790	9.730	0.92830^{2,3}
Bolivia	0	4.1700	13.880	15.760	19.710	0.93050^{2,3}	1	2.5700	5.470	6.790	9.730	0.41840^{1,2,3}
Brazil	0	4.9200	13.880	15.760	19.710	0.87690^{1,2,3}	1	3.5000	5.470	6.790	9.730	0.27080^{1,2,3}
Canada	0	5.3500	13.880	15.760	19.710	0.83920^{1,2,3}	1	2.9100	5.470	6.790	9.730	0.35780^{1,2,3}
Chile	0	3.6100	13.880	15.760	19.710	0.95970^{3}	1	1.5400	5.470	6.790	9.730	0.64920^{1,2,3}
Colombia	0	12.5100	13.880	15.760	19.710	0.15960^{1,2,3}	1	0.1200	5.470	6.790	9.730	0.99130
Costa Rica	0	10.6900	13.880	15.760	19.710	0.29560^{1,2,3}	1	0.2900	5.470	6.790	9.730	0.96510^{3}
Cuba	0	5.9500	13.880	15.760	19.710	0.78010^{1,2,3}	1	5.8500	5.470	6.790	9.730	0.08220^{1,2,3}
Dominica	0	13.0400	13.880	15.760	19.710	0.13360^{1,2,3}	1	2.3200	5.470	6.790	9.730	0.46760^{1,2,3}
Ecuador	0	10.9900	13.880	15.760	19.710	0.25620^{1,2,3}	1	1.0700	5.470	6.790	9.730	0.77390^{1,2,3}
El Salvador	0	3.9800	13.880	15.760	19.710	0.94170^{2,3}	1	0.2700	5.470	6.790	9.730	0.96790^{3}
Grenada	0	4.9500	13.880	15.760	19.710	0.87460^{1,2,3}	1	0.5700	5.470	6.790	9.730	0.90340^{2,3}
Guatemala	0	9.3300	13.880	15.760	19.710	0.40280^{1,2,3}	1	2.7800	5.470	6.790	9.730	0.38100^{1,2,3}
Guyana	0	4.1300	13.880	15.760	19.710	0.93300^{2,3}	1	0.8200	5.470	6.790	9.730	0.84050^{1,2,3}
Haiti	0	11.6400	13.880	15.760	19.710	0.21040^{1,2,3}	1	0.0900	5.470	6.790	9.730	0.99480
Honduras	0	10.7800	13.880	15.760	19.710	0.27190^{1,2,3}	1	0.0800	5.470	6.790	9.730	0.99510
Jamaica	0	6.8200	13.880	15.760	19.710	0.68400^{1,2,3}	1	2.9400	5.470	6.790	9.730	0.35340^{1,2,3}
Mexico	0	4.7100	13.880	15.760	19.710	0.89360^{1,2,3}	1	2.9800	5.470	6.790	9.730	0.34650^{1,2,3}
Nicaragua	0	5.9100	13.880	15.760	19.710	0.78410^{1,2,3}	1	2.5200	5.470	6.790	9.730	0.42850^{1,2,3}
Panama	0	8.4800	13.880	15.760	19.710	0.49260^{1,2,3}	1	3.6300	5.470	6.790	9.730	0.25450^{1,2,3}
Paraguay	0	5.6000	13.880	15.760	19.710	0.81580^{1,2,3}	1	2.9700	5.470	6.790	9.730	0.34850^{1,2,3}
Peru	0	6.7700	13.880	15.760	19.710	0.68990^{1,2,3}	1	2.9700	5.470	6.790	9.730	0.34890^{1,2,3}
Saint Lucia	0	5.1000	13.880	15.760	19.710	0.86220^{1,2,3}	1	0.8700	5.470	6.790	9.730	0.54460^{1,2,3}
Suriname	0	3.4600	13.880	15.760	19.710	0.96610^{3}	1	1.9700	5.470	6.790	9.730	0.82640^{1,2,3}
Tri. & Tob.	0	8.1100	13.880	15.760	19.710	0.53400^{1,2,3}	1	0.8500	5.470	6.790	9.730	0.83160^{1,2,3}
Uruguay	0	6.7800	13.880	15.760	19.710	0.68860^{1,2,3}	1	1.0300	5.470	6.790	9.730	0.78440^{1,2,3}
Venezuela	0	9.3500	13.880	15.760	19.710	0.40070^{1,2,3}	1	8.2800	5.470	6.790	9.730	0.02220^{1,2,3}
Algeria	0	7.9100	13.880	15.760	19.710	0.55750^{1,2,3}	1	2.1900	5.470	6.790	9.730	0.49580^{1,2,3}
Angola	0	3.8900	13.880	15.760	19.710	0.94620^{2,3}	1	0.2900	5.470	6.790	9.730	0.96550^{3}
Benin	0	6.3300	13.880	15.760	19.710	0.75390^{1,2,3}	1	3.5300	5.470	6.790	9.730	0.26670^{1,2,3}
Japan	0	5.9000	13.880	15.760	19.710	0.78510^{1,2,3}	1	3.7400	5.470	6.790	9.730	0.24060^{1,2,3}
Cameroon	0	10.5000	13.880	15.760	19.710	0.29480^{1,2,3}	1	1.0200	5.470	6.790	9.730	0.78700^{1,2,3}
Chad	0	3.5200	13.880	15.760	19.710	0.96350^{1,2,3}	1	1.5700	5.470	6.790	9.730	0.64200^{1,2,3}
Ivory Coast	0	15.0800	13.880	15.760	19.710	0.06460^{1,2,3}	1	0.7700	5.470	6.790	9.730	0.85280^{1,2,3}
Kenya	0	14.0600	13.880	15.760	19.710	0.09380^{1,2,3}	1	1.6700	5.470	6.790	9.730	0.61710^{1,2,3}
Liberia	0	4.2600	13.880	15.760	19.710	0.92500^{2,3}	1	1.7500	5.470	6.790	9.730	0.59770^{1,2,3}
Madagascar	0	8.8500	13.880	15.760	19.710	0.45280^{1,2,3}	1	0.9600	5.470	6.790	9.730	0.80280^{1,2,3}
Mauritania	0	7.2200	13.880	15.760	19.710	0.63800^{1,2,3}	1	4.1100	5.470	6.790	9.730	0.20007^{1,2,3}

Morocco	0	17.9600	13.880	15.760	19.710	0.02090[1,2,3]	1	3.0000	5.470	6.790	9.730	0.34340[1,2,3]
Niger	0	11.1300	13.880	15.760	19.710	0.24530[1,2,3]	1	0.2700	5.470	6.790	9.730	0.96890[3]
Rep. Congo	0	11.5400	13.880	15.760	19.710	0.21690[1,2,3]	1	0.5200	5.470	6.790	9.730	0.91710[2,3]
Senegal	0	12.6200	13.880	15.760	19.710	0.15370[1,2,3]	1	0.9300	5.470	6.790	9.730	0.81230[1,2,3]
South Afr.	0	4.5000	13.880	15.760	19.710	0.90870[2,3]	1	3.6900	5.470	6.790	9.730	0.24700[1,2,3]
Hong Kong	0	8.2900	13.880	15.760	19.710	0.51430[1,2,3]	1	0.0100	5.470	6.790	9.730	0.99990
India	0	11.4300	13.880	15.760	19.710	0.22450[1,2,3]	1	2.2900	5.470	6.790	9.730	0.47530[1,2,3]
Israel	0	3.6500	13.880	15.760	19.710	0.95810[3]	1	0.2500	5.470	6.790	9.730	0.97280[3]

Superscripts 1, 2, 3 show statistical significance at 90%, 95%, and 99% critical levels. LR = Likelihood Ratio

Eviews 7 was used to test for Granger causality. The Granger causality test proved that the US Granger causes emissions of the following economies: Bahamas, Canada, Ecuador, Guatemala, Jamaica, Mexico, Suriname, Madagascar, Morocco and Niger. Mexico registered a bidirectional causal link with US emissions. Note that a ρ–value less than the critical level of 0.05 ($\rho < 0.05$) represents causality in a given direction. Nicaragua's emissions were found to drive US emissions. Table 4 shows results of the Granger causality test for the US.

Table 4: Granger Causality Test Results (China)

Country	Causality	ρ-values[1]	Reverse Causality	ρ-values[1]
Argentina	$CO_2(ARG)_t \rightarrow CO_2(CHI)_{t(49)}$	$0.13150_{(2.1225)}$	$CO_2(CHI)_t \rightarrow CO_2(ARG)_{t(49)}$	$**0.00030_{(9.9618)}$
Bahamas	$CO_2(BAH)_t \rightarrow CO_2(CHI)_{t(49)}$	$0.84910_{(0.1642)}$	$CO_2(CHI)_t \rightarrow CO_2(BAH)_{t(49)}$	$0.35950_{(0.8491)}$
Barbados	$CO_2(BAR)_t \rightarrow CO_2(CHI)_{t(49)}$	$0.38590_{(0.9731)}$	$CO_2(CHI)_t \rightarrow CO_2(BAR)_{t(49)}$	$0.10300_{(2.3949)}$
Belize	$CO_2(BEL)_t \rightarrow CO_2(CHI)_{t(49)}$	$**0.00010_{(11.2390)}$	$CO_2(CHI)_t \rightarrow CO_2(BEL)_{t(49)}$	$0.08510_{(2.6073)}$
Bermuda	$CO_2(BER)_t \rightarrow CO_2(CHI)_{t(49)}$	$0.17940_{(1.8116)}$	$CO_2(CHI)_t \rightarrow CO_2(BER)_{t(49)}$	$0.66790_{(0.4073)}$
Bolivia	$CO_2(BOL)_t \rightarrow CO_2(CHI)_{t(49)}$	$0.83810_{(0.1773)}$	$CO_2(CHI)_t \rightarrow CO_2(BOL)_{t(49)}$	$0.37650_{(0.9989)}$
Brazil	$CO_2(BRA)_t \rightarrow CO_2(CHI)_{t(49)}$	$0.12160_{(2.2115)}$	$CO_2(CHI)_t \rightarrow CO_2(BRA)_{t(49)}$	$**0.01490_{(4.6363)}$
Canada	$CO_2(CAN)_t \rightarrow CO_2(CHI)_{t(49)}$	$0.54040_{(0.6241)}$	$CO_2(CHI)_t \rightarrow CO_2(CAN)_{t(49)}$	$0.692380_{(0.5058)}$
Chile	$CO_2(CHL)_t \rightarrow CO_2(CHI)_{t(49)}$	$0.13700_{(2.0804)}$	$CO_2(CHI)_t \rightarrow CO_2(CHL)_{t(49)}$	$**0.00540_{(5.8930)}$
Colombia	$CO_2(COL)_t \rightarrow CO_2(CHI)_{t(49)}$	$0.65790_{(0.4228)}$	$CO_2(CHI)_t \rightarrow CO_2(COL)_{t(49)}$	$**0.03870_{(3.5030)}$
Costa Rica	$CO_2(COS)_t \rightarrow CO_2(CHI)_{t(49)}$	$0.31290_{(1.1931)}$	$CO_2(CHI)_t \rightarrow CO_2(COS)_{t(49)}$	$0.31740_{(1.1782)}$
Cuba	$CO_2(CUB)_t \rightarrow CO_2(CHI)_{t(49)}$	$0.35550_{(1.0589)}$	$CO_2(CHI)_t \rightarrow CO_2(CUB)_{t(49)}$	$0.31000_{(1.2028)}$
Dominica	$CO_2(DOM)_t \rightarrow CO_2(CHI)_{t(49)}$	$**0.00000_{(13.2705)}$	$CO_2(CHI)_t \rightarrow CO_2(DOM)_{t(49)}$	$0.42180_{(0.8803)}$
Ecuador	$CO_2(ECU)_t \rightarrow CO_2(CHI)_{t(49)}$	$0.97550_{(0.0248)}$	$CO_2(CHI)_t \rightarrow CO_2(ECU)_{t(49)}$	$0.31690_{(1.1796)}$
El Salvador	$CO_2(ELS)_t \rightarrow CO_2(CHI)_{t(49)}$	$0.24160_{(1.4674)}$	$CO_2(CHI)_t \rightarrow CO_2(ELS)_{t(49)}$	$0.72840_{(0.3191)}$
Grenada	$CO_2(GRE)_t \rightarrow CO_2(CHI)_{t(49)}$	$0.33390_{(1.1248)}$	$CO_2(CHI)_t \rightarrow CO_2(GRE)_{t(49)}$	$0.20600_{(1.6380)}$
Guatemala	$CO_2(GUA)_t \rightarrow CO_2(CHI)_{t(49)}$	$**0.03360_{(3.6678)}$	$CO_2(CHI)_t \rightarrow CO_2(GUA)_{t(49)}$	$0.52370_{(0.6564)}$
Guyana	$CO_2(GUY)_t \rightarrow CO_2(CHI)_{t(49)}$	$0.75160_{(0.2874)}$	$CO_2(CHI)_t \rightarrow CO_2(GUY)_{t(49)}$	$0.88850_{(0.1186)}$
Haiti	$CO_2(HAI)_t \rightarrow CO_2(CHI)_{t(49)}$	$0.06030_{(2.9954)}$	$CO_2(CHI)_t \rightarrow CO_2(HAI)_{t(49)}$	$0.08060_{(2.6683)}$
Honduras	$CO_2(HON)_t \rightarrow CO_2(CHI)_{t(49)}$	$**0.00100_{(8.1281)}$	$CO_2(CHI)_t \rightarrow CO_2(HON)_{t(49)}$	$0.35710_{(1.0541)}$
Jamaica	$CO_2(JAM)_t \rightarrow CO_2(CHI)_{t(49)}$	$0.14830_{(1.9934)}$	$CO_2(CHI)_t \rightarrow CO_2(JAM)_{t(49)}$	$0.32090_{(1.1666)}$
Mexico	$CO_2(MEX)_t \rightarrow CO_2(CHI)_{t(49)}$	$0.85030_{(0.1627)}$	$CO_2(CHI)_t \rightarrow CO_2(MEX)_{t(49)}$	$0.34110_{(1.1024)}$
Nicaragua	$CO_2(NIC)_t \rightarrow CO_2(CHI)_{t(49)}$	$0.38250_{(0.9823)}$	$CO_2(CHI)_t \rightarrow CO_2(NIC)_{t(49)}$	$0.39920_{(0.9377)}$
Panama	$CO_2(PAN)_t \rightarrow CO_2(CHI)_{t(49)}$	$0.08160_{(2.6546)}$	$CO_2(CHI)_t \rightarrow CO_2(PAN)_{t(49)}$	$**0.00710_{(5.5565)}$
Paraguay	$CO_2(PAR)_t \rightarrow CO_2(CHI)_{t(49)}$	$0.96480_{(0.0359)}$	$CO_2(CHI)_t \rightarrow CO_2(PAR)_{t(49)}$	$0.08570_{(2.6000)}$
Peru	$CO_2(PER)_t \rightarrow CO_2(CHI)_{t(49)}$	$0.43140_{(0.8569)}$	$CO_2(CHI)_t \rightarrow CO_2(PER)_{t(49)}$	$**0.00110_{(8.0444)}$
Saint Lucia	$CO_2(SAI)_t \rightarrow CO_2(CHI)_{t(49)}$	$0.23020_{(1.5188)}$	$CO_2(CHI)_t \rightarrow CO_2(SAI)_{t(49)}$	$0.60210_{(0.5133)}$
Suriname	$CO_2(SUR)_t \rightarrow CO_2(CHI)_{t(49)}$	$0.37310_{(1.0084)}$	$CO_2(CHI)_t \rightarrow CO_2(SUR)_{t(49)}$	$0.44940_{(0.8146)}$
Tri. & Tob.	$CO_2(TRI)_t \rightarrow CO_2(CHI)_{t(49)}$	$0.22330_{(1.5515)}$	$CO_2(CHI)_t \rightarrow CO_2(TRI)_{t(49)}$	$**0.00390_{(1.5515)}$

Uruguay	$CO_2(URU)_t \rightarrow CO_2(CHI)_{t(49)}$	$0.89830_{(0.1075)}$	$CO_2(CHI)_t \rightarrow CO_2(URU)_{t(49)}$	$0.31160_{(1.1976)}$
Venezuela	$CO_2(VEN)_t \rightarrow CO_2(CHI)_{t(49)}$	$**0.00620_{(5.7271)}$	$CO_2(CHI)_t \rightarrow CO_2(VEN)_{t(49)}$	$**0.00790_{(5.4120)}$
Algeria	$CO_2(ALG)_t \rightarrow CO_2(CHI)_{t(49)}$	$0.61900_{(0.4849)}$	$CO_2(CHI)_t \rightarrow CO_2(ALG)_{t(49)}$	$0.10690_{(2.3537)}$
Angola	$CO_2(ANG)_t \rightarrow CO_2(CHI)_{t(49)}$	$0.74170_{(0.3008)}$	$CO_2(CHI)_t \rightarrow CO_2(ANG)_{t(49)}$	$**0.00010_{(11.458)}$
Benin	$CO_2(BEN)_t \rightarrow CO_2(CHI)_{t(49)}$	$0.06210_{(2.9614)}$	$CO_2(CHI)_t \rightarrow CO_2(BEN)_{t(49)}$	$0.06100_{(2.9828)}$
Japan	$CO_2(JAP)_t \rightarrow CO_2(CHI)_{t(49)}$	$0.96650_{(0.0341)}$	$CO_2(CHI)_t \rightarrow CO_2(JAP)_{t(49)}$	$0.20620_{(1.6371)}$
Cameroon	$CO_2(CAM)_t \rightarrow CO_2(CHI)_{t(49)}$	$0.88610_{(0.1213)}$	$CO_2(CHI)_t \rightarrow CO_2(CAM)_{t(49)}$	$0.06760_{(2.8663)}$
Chad	$CO_2(CHA)_t \rightarrow CO_2(CHI)_{t(49)}$	$0.20830_{(1.6262)}$	$CO_2(CHI)_t \rightarrow CO_2(CHA)_{t(49)}$	$0.21390_{(1.5977)}$
Ivory Coast	$CO_2(IVO)_t \rightarrow CO_2(CHI)_{t(49)}$	$0.16460_{(1.8803)}$	$CO_2(CHI)_t \rightarrow CO_2(IVO)_{t(49)}$	$2.91364_{(0.0648)}$
Kenya	$CO_2(KEN)_t \rightarrow CO_2(CHI)_{t(49)}$	$0.25670_{(1.4030)}$	$CO_2(CHI)_t \rightarrow CO_2(KEN)_{t(49)}$	$**0.00170_{(7.3977)}$
Liberia	$CO_2(LIB)_t \rightarrow CO_2(CHI)_{t(49)}$	$0.90790_{(0.0968)}$	$CO_2(CHI)_t \rightarrow CO_2(LIB)_{t(49)}$	$0.13510_{(2.0954)}$
Madagascar	$CO_2(MAD)_t \rightarrow CO_2(CHI)_{t(49)}$	$0.09430_{(2.4925)}$	$CO_2(CHI)_t \rightarrow CO_2(MAD)_{t(49)}$	$**0.03800_{(3.5266)}$
Mauritania	$CO_2(MAU)_t \rightarrow CO_2(CHI)_{t(49)}$	$0.25820_{(1.3965)}$	$CO_2(CHI)_t \rightarrow CO_2(MAU)_{t(49)}$	$0.51530_{(0.6731)}$
Morocco	$CO_2(MOR)_t \rightarrow CO_2(CHI)_{t(49)}$	$**0.04710_{(3.2773)}$	$CO_2(CHI)_t \rightarrow CO_2(MOR)_{t(49)}$	$**0.00002_{(13.988)}$
Niger	$CO_2(NIG)_t \rightarrow CO_2(CHI)_{t(49)}$	$0.65610_{(0.4255)}$	$CO_2(CHI)_t \rightarrow CO_2(NIG)_{t(49)}$	$0.05640_{(3.0717)}$
Rep. Congo	$CO_2(ROC)_t \rightarrow CO_2(CHI)_{t(49)}$	$0.24070_{(1.4715)}$	$CO_2(CHI)_t \rightarrow CO_2(ROC)_{t(49)}$	$0.07520_{(2.7463)}$

Table 4 (continued)

Country	Causality	ρ-values[1]	Reverse Causality	ρ-values[1]
Senegal	$CO_2(SEN)_t \rightarrow CO_2(CHI)_{t(49)}$	$0.80170_{(0.2221)}$	$CO_2(CHI)_t \rightarrow CO_2(SEN)_{t(49)}$	$**0.01470_{(4.6522)}$
South Africa	$CO_2(SA)_t \rightarrow CO_2(CHI)_{t(49)}$	$0.12570_{(2.1750)}$	$CO_2(CHI)_t \rightarrow CO_2(SA)_{t(49)}$	$0.40960_{(0.9110)}$
Hong Kong	$CO_2(HK)_t \rightarrow CO_2(CHI)_{t(49)}$	$0.96750_{(0.0331)}$	$CO_2(CHI)_t \rightarrow CO_2(HK)_{t(49)}$	$0.77510_{(0.2562)}$
India	$CO_2(IND)_t \rightarrow CO_2(CHI)_{t(49)}$	$0.15580_{(1.9400)}$	$CO_2(CHI)_t \rightarrow CO_2(IND)_{t(49)}$	$**0.00010_{(11.515)}$
Israel	$CO_2(ISR)_t \rightarrow CO_2(CHI)_{t(49)}$	$0.07333_{(2.7741)}$	$CO_2(CHI)_t \rightarrow CO_2(ISR)_{t(49)}$	$0.55140_{(0.6033)}$

$CO_2(a)_t \leftrightarrow CO_2(b)_{t(49)}$ In this causal relationship, a and b represent the country codes and subscript 49 is the number of observations used in the causality analysis as from 1960 to 2010. Subscript next to the ρ–value is the F-statistic. Superscript (1) represents the ρ–value at 5% critical level. Asterisks (**) represent a causal relation.

Further causality analysis was carried out between China's emissions and other economies carbon discharges. The Chinese economy was found to Granger cause the following economies emissions: Argentina, Brazil, Chile, Colombia, Panama, Peru, Trinidad and Tobago, Venezuela, Angola, Kenya, Madagascar, Morocco, Senegal and India. Alternatively, the following economies were leading China's emissions: Belize, Dominica, Guatemala, Honduras, Venezuela and Morocco. Note that a ρ–value less than the critical level of 0.05 ($\rho < 0.05$) represents a causal link in a particular direction. Table 5 shows results of the Granger causality test.

Table 5: Granger Causality Test Results (US)

Country	Causality	ρ-values[1]	Reverse Causality	ρ-values[1]
Argentina	$CO_2(ARG)_t \rightarrow CO_2(US)_{t(49)}$	$0.79700_{(0.2281)}$	$CO_2(US)_t \rightarrow CO_2(ARG)_{t(49)}$	$0.30860_{(1.2079)}$
Bahamas	$CO_2(BAH)_t \rightarrow CO_2(US)_{t(49)}$	$0.08050_{(2.6691)}$	$CO_2(US)_t \rightarrow CO_2(BAH)_{t(49)}$	$^{**}0.00333_{(3.6793)}$
Barbados	$CO_2(BAR)_t \rightarrow CO_2(US)_{t(49)}$	$0.46420_{(0.7810)}$	$CO_2(US)_t \rightarrow CO_2(BAR)_{t(49)}$	$0.22010_{(1.5670)}$
Belize	$CO_2(BEL)_t \rightarrow CO_2(US)_{t(49)}$	$0.38380_{(0.9789)}$	$CO_2(US)_t \rightarrow CO_2(BEL)_{t(49)}$	$0.06320_{(2.9425)}$
Bermuda	$CO_2(BER)_t \rightarrow CO_2(US)_{t(49)}$	$0.82510_{(0.1931)}$	$CO_2(US)_t \rightarrow CO_2(BER)_{t(49)}$	$0.31940_{(1.1713)}$
Bolivia	$CO_2(BOL)_t \rightarrow CO_2(US)_{t(49)}$	$0.11390_{(2.2836)}$	$CO_2(US)_t \rightarrow CO_2(BOL)_{t(49)}$	$0.69100_{(0.3727)}$
Brazil	$CO_2(BRA)_t \rightarrow CO_2(US)_{t(49)}$	$0.34230_{(1.0987)}$	$CO_2(US)_t \rightarrow CO_2(BRA)_{t(49)}$	$0.52730_{(0.6495)}$
Canada	$CO_2(CAN)_t \rightarrow CO_2(US)_{t(49)}$	$0.54810_{(0.6097)}$	$CO_2(US)_t \rightarrow CO_2(CAN)_{t(49)}$	$^{**}0.00140_{(7.6520)}$
Chile	$CO_2(CHL)_t \rightarrow CO_2(US)_{t(49)}$	$0.59090_{(0.5324)}$	$CO_2(US)_t \rightarrow CO_2(CHL)_{t(49)}$	$0.98230_{(0.0179)}$
Colombia	$CO_2(COL)_t \rightarrow CO_2(US)_{t(49)}$	$0.17450_{(1.8172)}$	$CO_2(US)_t \rightarrow CO_2(COL)_{t(49)}$	$0.65700_{(0.4241)}$
Costa Rica	$CO_2(COS)_t \rightarrow CO_2(US)_{t(49)}$	$0.86050_{(0.1507)}$	$CO_2(US)_t \rightarrow CO_2(COS)_{t(49)}$	$0.32010_{(1.1691)}$
Cuba	$CO_2(CUB)_t \rightarrow CO_2(US)_{t(49)}$	$0.40870_{(0.9132)}$	$CO_2(US)_t \rightarrow CO_2(CUB)_{t(49)}$	$0.34430_{(1.0926)}$
Dominica	$CO_2(DOM)_t \rightarrow CO_2(US)_{t(49)}$	$0.40880_{(0.9129)}$	$CO_2(US)_t \rightarrow CO_2(DOM)_{t(49)}$	$0.39570_{(0.9469)}$
Ecuador	$CO_2(ECU)_t \rightarrow CO_2(US)_{t(49)}$	$0.83420_{(0.1821)}$	$CO_2(US)_t \rightarrow CO_2(ECU)_{t(49)}$	$^{**}0.04770_{(3.2641)}$
El Salvador	$CO_2(ELS)_t \rightarrow CO_2(US)_{t(49)}$	$0.12170_{(2.2099)}$	$CO_2(US)_t \rightarrow CO_2(ELS)_{t(49)}$	$0.40410_{(0.9249)}$
Grenada	$CO_2(GRE)_t \rightarrow CO_2(US)_{t(49)}$	$0.36620_{(1.0280)}$	$CO_2(US)_t \rightarrow CO_2(GRE)_{t(49)}$	$0.83230_{(0.1843)}$
Guatemala	$CO_2(GUA)_t \rightarrow CO_2(US)_{t(49)}$	$0.30980_{(1.2035)}$	$CO_2(US)_t \rightarrow CO_2(GUA)_{t(49)}$	$^{**}0.00640_{(5.6711)}$
Guyana	$CO_2(GUY)_t \rightarrow CO_2(US)_{t(49)}$	$0.59490_{(0.5255)}$	$CO_2(US)_t \rightarrow CO_2(GUY)_{t(49)}$	$0.75210_{(0.2867)}$
Haiti	$CO_2(HAI)_t \rightarrow CO_2(US)_{t(49)}$	$0.98270_{(0.0175)}$	$CO_2(US)_t \rightarrow CO_2(HAI)_{t(49)}$	$0.09150_{(2.5263)}$
Honduras	$CO_2(HON)_t \rightarrow CO_2(US)_{t(49)}$	$0.77590_{(0.2552)}$	$CO_2(US)_t \rightarrow CO_2(HON)_{t(49)}$	$0.20220_{(1.6583)}$
Jamaica	$CO_2(JAM)_t \rightarrow CO_2(US)_{t(49)}$	$0.41610_{(0.8945)}$	$CO_2(US)_t \rightarrow CO_2(JAM)_{t(49)}$	$^{**}0.00220_{(7.0427)}$
Mexico	$CO_2(MEX)_t \rightarrow CO_2(US)_{t(49)}$	$^{**}0.01890_{(4.547)}$	$CO_2(US)_t \rightarrow CO_2(MEX)_{t(49)}$	$^{**}0.00110_{(7.9402)}$
Nicaragua	$CO_2(NIC)_t \rightarrow CO_2(US)_{t(49)}$	$^{**}0.03300_{(3.689)}$	$CO_2(US)_t \rightarrow CO_2(NIC)_{t(49)}$	$0.35300_{(1.0662)}$
Panama	$CO_2(PAN)_t \rightarrow CO_2(US)_{t(49)}$	$0.34460_{(1.0916)}$	$CO_2(US)_t \rightarrow CO_2(PAN)_{t(49)}$	$0.68300_{(0.3846)}$
Paraguay	$CO_2(PAR)_t \rightarrow CO_2(US)_{t(49)}$	$0.20990_{(1.6178)}$	$CO_2(US)_t \rightarrow CO_2(PAR)_{t(49)}$	$0.91940_{(0.0842)}$
Peru	$CO_2(PER)_t \rightarrow CO_2(US)_{t(49)}$	$0.79770_{(0.2272)}$	$CO_2(US)_t \rightarrow CO_2(PER)_{t(49)}$	$0.28030_{(1.3092)}$
Saint Lucia	$CO_2(SAI)_t \rightarrow CO_2(US)_{t(49)}$	$0.31320_{(1.1921)}$	$CO_2(US)_t \rightarrow CO_2(SAI)_{t(49)}$	$0.29370_{(1.2600)}$
Suriname	$CO_2(SUR)_t \rightarrow CO_2(US)_{t(49)}$	$0.41120_{(0.9069)}$	$CO_2(US)_t \rightarrow CO_2(SUR)_{t(49)}$	$^{**}0.03010_{(3.7969)}$
Tri. & Tob.	$CO_2(TRI)_t \rightarrow CO_2(US)_{t(49)}$	$0.92780_{(0.0751)}$	$CO_2(US)_t \rightarrow CO_2(TRI)_{t(49)}$	$0.10920_{(2.3293)}$
Uruguay	$CO_2(URU)_t \rightarrow CO_2(US)_{t(49)}$	$0.44050_{(0.8352)}$	$CO_2(US)_t \rightarrow CO_2(URU)_{t(49)}$	$0.12890_{(2.1475)}$
Venezuela	$CO_2(VEN)_t \rightarrow CO_2(US)_{t(49)}$	$0.21830_{(1.5755)}$	$CO_2(US)_t \rightarrow CO_2(VEN)_{t(49)}$	$0.34820_{(1.0808)}$
Algeria	$CO_2(ALG)_t \rightarrow CO_2(US)_{t(49)}$	$0.68850_{(0.3764)}$	$CO_2(US)_t \rightarrow CO_2(ALG)_{t(49)}$	$0.51230_{(0.6790)}$
Angola	$CO_2(ANG)_t \rightarrow CO_2(US)_{t(49)}$	$0.70730_{(0.3491)}$	$CO_2(US)_t \rightarrow CO_2(ANG)_{t(49)}$	$0.79730_{(0.2278)}$
Benin	$CO_2(BEN)_t \rightarrow CO_2(US)_{t(49)}$	$0.14940_{(1.9879)}$	$CO_2(US)_t \rightarrow CO_2(BEN)_{t(49)}$	$0.64880_{(0.4371)}$
Japan	$CO_2(JAP)_t \rightarrow CO_2(US)_{t(49)}$	$0.30330_{(1.2261)}$	$CO_2(US)_t \rightarrow CO_2(JAP)_{t(49)}$	$0.24430_{(1.4556)}$
Cameroon	$CO_2(CAM)_t \rightarrow CO_2(US)_{t(49)}$	$0.11760_{(2.2484)}$	$CO_2(US)_t \rightarrow CO_2(CAM)_{t(49)}$	$0.06210_{(2.9618)}$
Chad	$CO_2(CHA)_t \rightarrow CO_2(US)_{t(49)}$	$0.63340_{(0.4614)}$	$CO_2(US)_t \rightarrow CO_2(CHA)_{t(49)}$	$0.36240_{(1.0387)}$
Ivory Coast	$CO_2(IVO)_t \rightarrow CO_2(US)_{t(49)}$	$0.90150_{(0.1039)}$	$CO_2(US)_t \rightarrow CO_2(IVO)_{t(49)}$	$0.13620_{(2.0871)}$
Kenya	$CO_2(KEN)_t \rightarrow CO_2(US)_{t(49)}$	$0.70180_{(0.3569)}$	$CO_2(US)_t \rightarrow CO_2(KEN)_{t(49)}$	$0.12390_{(2.1906)}$
Liberia	$CO_2(LIB)_t \rightarrow CO_2(US)_{t(49)}$	$0.11940_{(2.2316)}$	$CO_2(US)_t \rightarrow CO_2(LIB)_{t(49)}$	$0.14280_{(2.0353)}$
Madagascar	$CO_2(MAD)_t \rightarrow CO_2(US)_{t(49)}$	$0.55490_{(0.5970)}$	$CO_2(US)_t \rightarrow CO_2(MAD)_{t(49)}$	$^{**}0.00220_{(7.0332)}$
Mauritania	$CO_2(MAU)_t \rightarrow CO_2(US)_{t(49)}$	$0.64550_{(0.4422)}$	$CO_2(US)_t \rightarrow CO_2(MAU)_{t(49)}$	$0.49220_{(0.7201)}$
Morocco	$CO_2(MOR)_t \rightarrow CO_2(US)_{t(49)}$	$0.51040_{(0.6830)}$	$CO_2(US)_t \rightarrow CO_2(MOR)_{t(49)}$	$^{**}0.03440_{(3.6402)}$
Niger	$CO_2(NIG)_t \rightarrow CO_2(US)_{t(49)}$	$0.61300_{(0.4950)}$	$CO_2(US)_t \rightarrow CO_2(NIG)_{t(49)}$	$^{**}0.00600_{(5.7592)}$
Rep. Congo	$CO_2(ROC)_t \rightarrow CO_2(US)_{t(49)}$	$0.11000_{(2.3219)}$	$CO_2(US)_t \rightarrow CO_2(ROC)_{t(49)}$	$0.21990_{(1.5680)}$

Table 5 (continued)

Country	Causality	ρ-values[1]	Reverse Causality	ρ-values[1]
Senegal	$CO_2(SEN)_t \rightarrow CO_2(US)_{t(49)}$	$0.42900_{(0.8629)}$	$CO_2(US)_t \rightarrow CO_2(SEN)_{t(49)}$	$0.12520_{(2.1792)}$
South Africa	$CO_2(SA)_t \rightarrow CO_2(US)_{t(49)}$	$0.46930_{(0.8000)}$	$CO_2(US)_t \rightarrow CO_2(SA)_{t(49)}$	$0.35270_{(1.0671)}$
Hong Kong	$CO_2(HK)_t \rightarrow CO_2(US)_{t(49)}$	$0.26970_{(1.3504)}$	$CO_2(US)_t \rightarrow CO_2(HK)_{t(49)}$	$0.67830_{(0.3916)}$
India	$CO_2(IND)_t \rightarrow CO_2(US)_{t(49)}$	$0.24390_{(1.4572)}$	$CO_2(US)_t \rightarrow CO_2(IND)_{t(49)}$	$0.51670_{(0.6703)}$
Israel	$CO_2(ISR)_t \rightarrow CO_2(US)_{t(49)}$	$0.18080_{(1.1779)}$	$CO_2(US)_t \rightarrow CO_2(ISR)_{t(49)}$	$0.42120_{(0.8818)}$

$CO_2(a)_t \leftrightarrow CO_2(b)_{t(49)}$ In this causal relationship, a and b represent the country codes and subscript 49 is the number of observations used in the causality analysis as from 1960 to 2010. Subscript next to the ρ–value is the F-statistic. Superscript (1) represents the ρ–value at 5% critical level. Asterisks (**) represent a causal relation.

5 Discussion and Conclusion

This investigation aimed to determine the relationships between the US, China and other economies carbon dioxide emissions between 1960 and 2010. Previous studies generally channelled much attention to validating the relations between economic growth, energy consumption, and carbon dioxide emissions. The present literature generally applied cointegration and causality tests in the analysis of carbon dioxide emissions, economic growth and energy consumption. This paper aimed to provide links between the top economies carbon dioxide production and diverse economies' discharges. The underlying idea is that robust economies such as the US and China produce enormous emissions during exports production. As a result, many economies import from these economies products with high technological content in their attempts to industrialise. The total effect is that these economies will produce more carbon dioxide as their industrialisation attempts rise. This paper viewed this process as a causal link, were high income economies drive other countries carbon dioxide emissions. Reducing emissions can be achieved by reducing energy consumption of fossil fuels; using alternative energy sources; minimizing output production and green taxation. These factors however, can impinge negatively on economic growth.

The results of this study have shown that all economies under examination trend positively with both China and the US in terms of carbon dioxide emissions. This is not surprising especially for China which is the largest emitter of carbon dioxide and the most influential contributor to the greenhouse effect. The Granger causality test results demonstrated that the US Granger causes ten economies carbon dioxide emissions namely: Bahamas, Canada, Ecuador, Guatemala, Jamaica, Mexico, Suriname, Madagascar, Morocco and Niger. Drawing from the results, Nicaragua is leading US emissions as from 1960 to 2010. Interestingly, Mexico was the only economy which demonstrated bidirectional causal links with US emissions. Statistically, China was leading carbon emissions of the following countries: Argentina, Brazil, Chile, Colombia, Panama, Peru, Trinidad and Tobago, Venezuela, Angola, Kenya, Madagascar, Morocco, Senegal and India. However, the reverse causality demonstrated that the following economies were driving Chinese emissions: Belize, Dominica, Guatemala and Honduras. Additionally, Venezuela and Morocco revealed bidirectional causal links with Chinese carbon dioxide discharges.

The results of this study are inclined to be affected by several factors. Firstly, the US has been the largest economy in the world for a considerable length of time therefore her influence is expected to be robust globally. All countries exhibited long term affiliations with the US carbon emissions. Nonetheless, the Granger causality test affirmed that only Mexico and Nicaragua have significant effects on US emissions. Practically, an economy cannot be self-sufficient in all sectors. There is a need to import some products from other countries such as Mexico. This possibly explains the bidirectional causal link. In the case of China, the long term affiliations between carbon dioxide emissions depict the world's dependence on Chinese exports to a reasonable extent. Despite this, Chinese emissions are affected by other economies emissions. China has more countries having an effect on her emissions than the US. The possible explanation is that China has been developing over time and this transition involved dependence on other nations. This may further explain China's high economic growth, commencing as one of the weakest economies in the world to become the world's second largest economy.

In conclusion of this study, the results have demonstrated that China and the US drive numerous economies emissions as anticipated. The results are plausible because the US and China have massive impact on the world's macroeconomic factors such as interest rates, exports and exchange rates. However, this relationship carries implications. Possessing enormous effect on other countries' emissions means that the responsibility to speed up emissions reduction also becomes your sense of duty. The Chinese government should be commended for intending to cut emissions by 40-45% by 2025 and setting up carbon dioxide monitoring satellites in 2016.

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